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ABSTRACT

This paper re-examines the relationship between financial variables and real activity in a unified statistical framework. Using the methods of cointegration and separation, we characterize the long-run and short-run relationships between three sets of variables and then use the framework to assess the predictive power of alternative financial variables for real activity. Three main results emerge from the analysis. First, we show that although two sets of variables may not share the long-run trend, the error correction terms from one set of variables may have important explanatory power for the variables in another set. Second, we show that some of the key variables discussed in the literature can be interpreted as error correction terms from another system. Third, comparing two key error correction terms, M2 velocity and the interest rate spread between commercial paper and Treasury bills, we find that M2 velocity appears to be a more consistent predictor of output than is the interest rate spread.

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The empirical relationship between financial variables and the real economy is hardly a new area of research. Yet a resurgence of interest in this topic in the last few years has uncovered several striking new characteristics of the data. First, several authors have argued that the single most significant financial variable for predicting real activity is the interest rate spread between six month commercial paper and Treasury bills (e.g., Stock and Watson (1989), Friedman and Kuttner (1992), Bernanke (1990)). Second, many different studies in the last decade have found that when interest rates are included, monetary aggregates no longer have much predictive power for future economic activity (e.g. Sims (1980), Litterman and Weiss (1985), Friedman and Kuttner (1992)). Third, a number of studies have found that balance sheet variables show certain patterns before recessions. For example, Kashyap, Stein and Wilcox (1991) (KSW) have found that firms increase their use of commercial paper borrowing relative to bank borrowing after a monetary tightening. These new empirical results have led to renewed speculation on the indicators of monetary policy and the link between the financial sector and real activity.

This paper re-examines the relationship between financial variables and real activity in a unified statistical framework. The statistical framework, which uses the concepts of cointegration and separation introduced by Granger and Konishi (1991), permits a systematic characterization of the relationships between several sets of variables as well as a distinction between linkages in the long-run and in the short-run. The framework is used to study the predictive power of alternative financial variables for real activity.

Three main results emerge from the analysis. The first result concerns the specification of models when the variables appear to have unit roots. We show that although two sets of variables may not share the same long-run trend, the error correction terms from one set of variables may have important explanatory power for the variables in another set. One can think of this concept as extending the usual "partial equilibrium" cointegration framework to a more "general equilibrium" setting. The second result is that several of the new variables discussed in the literature can be interpreted as error correction terms from another system. In particular, the interest rate spread is the error correction term from the interest rate sector, while a transformation of Kashyap et al.'s mix variable is an error correction term from the credit aggregate sector. The third set of results concerns the relative importance of the predictive power of monetary aggregates versus interest rates. Following up on our analysis on the information in error correction terms, we investigate the predictive power of the error correction term between money (M2) and output, i.e. velocity. In quarterly data from 1960 to 1991, velocity is highly significant in predicting both real GNP growth and real fixed investment growth, even after interest rate terms are included. Furthermore, the predictive power of velocity is much more stable over different sample periods than the predictive power of the interest rate variables. We uncover the surprising result that most of the explanatory power of interest rate spread comes from the five year period 1971 - 1975. If that period is omitted in the estimation, interest rate spreads no longer Granger cause output at conventional significance levels.

1. Econometric Framework

It was clear from the earliest work developing cointegration that a useful formulation used common stochastic trends, as mention in Granger (1986) and further developed in

Stock and Watson (1988) and Gonzalo and Granger (1991). Suppose that $\underline{x}_t$ is a vector with n components which can be written as

$$\underline{x}_t = \underset{(n\times m)}{\underline{A}} \underline{w}_t + \underline{a}_t \tag{1.1}$$

where $\underline{w}_t$ is a vector of $m=n-r$ I(1) components which are not cointegrated and $\underline{a}_t$ is a vector of I(0) components. It follows that there will be a matrix of $\underline{\alpha}$ of rank r, known as the cointegration matrix, such that $\underline{z}_t = \underline{\alpha}' \underline{x}_t$ is a vector of r I(0) components.

A special case of some particular interest, called separation cointegration, is discussed by Granger and Konishi (1992), in which two groups of variables may be unrelated in the long-run. Suppose that these two groups are $\underline{x}_{1t}$, $\underline{x}_{2t}$ consisting of n_2 and n_2 variables and with cointegration of ranks r_1, r_2 respectively. Suppose further that these can be written as

$$\underline{x}_{1t} = \underline{A}_1 \underline{w}_{1t} + \underline{a}_{1t} \tag{1.2}$$

$$\underline{x}_{2t} = \underline{A}_2 \underline{w}_{2t} + \underline{a}_{2t} \tag{1.3}$$

where $\underline{A}_i$ is $n_i \times m_i$, $m_i = n_i - r_i$, $i = 1,2$ and that no component in $\underline{w}_{1t}$ is cointegrated with $\underline{w}_{2t}$, so that in particular, no common trend occurs in both $\underline{w}_{1t}$ and $\underline{w}_{2t}$. Thus, the two groups have separate common trends. It follows that $r = r_1 + r_2$ is $\underline{x}_t$ consists of $\underline{x}_{1t}$ and $\underline{x}_{2t}$, so that $m = m_1 + m_2$. Thus, there is no relationship in the long-run, but there can be relatedness in the short run, and $\underline{a}_t$, consisting of $\underline{a}_{1t}$ and $\underline{a}_{2t}$ may be generated by a full n-dimension vector autoregression, for example.

We can formulate this possibility in the form of the following error correction model:

$$\begin{pmatrix} \Delta X_{1t} \\ \Delta X_{2t} \end{pmatrix} = \begin{pmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{pmatrix} \begin{pmatrix} \alpha_1' & 0 \\ 0 & \alpha_2' \end{pmatrix} \begin{pmatrix} X_{1t-1} \\ X_{2t-1} \end{pmatrix} + \begin{pmatrix} \Gamma_{11}(L) & \Gamma_{12}(L) \\ \Gamma_{21}(L) & \Gamma_{22}(L) \end{pmatrix} \begin{pmatrix} \Delta X_{1t-1} \\ \Delta X_{2t-1} \end{pmatrix} + d + v_t \tag{1.4}$$

where $$\Gamma_{ij}(L)=\sum_{m=1}^{k}\Gamma_{ij}^{m}L^{j}.$$

Unless $\gamma_{12} = \gamma_{21} = 0$, the error correction term (or disequilibrium term) of one block affects the other block. In this sense, equation (1-4) can be interpreted as 'general equilibrium' cointegration since $\alpha_1'X_{1t} = \alpha_2'X_{2t} = 0$ is needed for the whole system to reach equilibria.

To test this hypothesis, we need to test the following restruction on the cointegration space:

$$H_0 : \alpha = \begin{pmatrix} H_1 \underset{n\times r_1}{\varphi_1} & H_2 \underset{n\times r_2}{\varphi_2} \end{pmatrix} \tag{1.5}$$

where $H_1=(I_{n_1} \quad 0), H_2=(0 \quad I_{n_2})$

that is, the cointegration space α can be block diagonalized into two sub-spaces φ_1 and φ_2. However, to perform this test, one needs to have a prior knowledge on the ranks of cointegration (r_1,r_2,r). Further it is also necessary to conduct a cointegration test to make sure that $r=r_1+r_2$ holds, so that no additional cointegrating vector should be found. Under this condition, the hypothesis (1.5) can be tested in the following manner;

Let $R_{0t}^{i}=\Delta X_t - Z_{jt}(Z_{jt}'Z_{jt})^{-1}(Z_{jt}'\ \Delta X_t)$ and

$R_{kt}^{i}=X_{it-1} - Z_{jt}(Z_{jt}'Z_{jt})^{-1}(Z_{jt}'X_{it-1}) \quad i=1,2$

where $Z_{it}=(\Delta X_{it-1},\ldots,\Delta X_{it-k},\Delta X_{2t-1},\ldots,\Delta X_{2t-k},\varphi_j'H_j'X_{t-1}) \quad i = 1,2$

Further, define

$$S_{1m}^{i} = \frac{1}{T}\sum_{t=1}^{T} R_{1t}^{i}\, R_{mt}^{i\,\prime} \quad i=1,\ 2;\ m=0,\ldots,\ k$$

Granger and Konishi show that φ_i $(i=1,2)$ are obtained as r_i eigenvectors corresponding to the r_i largest eigenvalues of the following equation

$$| \gamma^i S^i_{kk} - S^i_{k0} (S^i_{00})^{-1} S^i_{0k} | = 0 \tag{1.6}$$

The paper suggests the algorithm starts with the value of zero for one of φ_i and reiterates the calculation of (1-5). If there is convergence, the test statistics are obtained as follows:

$$Q = -T \left(\sum_{j=1}^{r_k} \ln(1-\hat{\gamma}_j^k) + \sum_{j=1}^{r_m} \ln(1 - \hat{\rho}_j^m) - \sum_{j=1}^{r} \ln (1 - \hat{\gamma}_i)\right) \tag{1.7}$$
$$k,m=1,2, \quad k \neq m$$

where $\hat{\rho}_j^m$ is the eigenvector associated with the j -th largest eigenvalue of

$$| \rho^i \hat{\varphi}_i' H_i' S_{kk} \hat{\varphi}_i H_i - \hat{\varphi}_i' H_i' S_{k0} \hat{\varphi}_i H_i | = 0 \tag{1.8}$$

also $\hat{\gamma}_j$ is the eigenvector associated with the j - th largest eigenvalue of

$$| \gamma S_{kk} - S_{k0} (S_{00})^{-1} S_{0k} | = 0 \tag{1.9}$$

where $S_{lm} = \frac{1}{T}\sum_{t=1}^{T} R_{lt} R_{mt}' \qquad l,m = 0,k$

R_{0t}, R_{kt} are the residuals of the regressions of ΔX_t and X_{t-1} against $\Delta X_{t-1} \ldots,\ \ \Delta X_{t-k}$ respectively.

The paper finally shows that under the null, the test statistics have an asymptotic distribution of χ^2 with $(n_1-r_1)r_2 + (n_2-r_2)r_1$ degrees of freedom.

Separation gives us an interesting interpretation of the common factor representation. As stated above, under the separation hypothesis, the common factor representation of $X_t = (X_{1t}', X_{2t}')'$ can be expressed as (1.4), where η_{it} and ϵ_{it} are stationary.

It is interesting to see that even under separate cointegration, those two groups of variables may be related to each other. Let $\gamma_{ii}^{\perp}$ be the space orthogonal to γ_{ii} . According to the Gonzalo-Granger representation,

$$\eta_{it} = \gamma_{ii}^{\perp\prime} \Delta X_{it} \quad i = 1,2$$

Then

$$\eta_{it} = \gamma_{ii}^{\perp\prime}(\Gamma_{ii}(L)\Delta X_{it} + \Gamma_{ij}(L)\Delta X_{jt}) + \gamma_{ii}^{\perp\prime}\gamma_{ij}\alpha_j^{\prime}X_{jt-1} \quad i = 1,2 \tag{1.10}$$

that is, if the error correction term of one block affects the change of the other block it should affect the innovation of common trends of the other block, not only the transitory part in general. This is why the error correction term of one block can be so informative and important on the future movement of the other block. By estimating the error correction model (1-4), we can simply estimate the component of variations in the common factors.

To estimate common factors, it is necessary to know $\gamma_{ii}^{\perp}$, a space orthogonal to the adjustment coefficient. Granger and Konishi (1992) show the estimation procedure by taking advantage of Johansen (1988)'s results on the duality of estimating $\gamma_{ii}^{\perp}$ and α (the cointegrating vector). $\gamma_{ii}^{\perp}$ can be found as eigenvectors associated with the smallest n_i-r_i eigenvalues of the following equation:

$$|\gamma^i S_{00}^i - S_{0-k}^i(S_{kk}^i)^{-1}S_{k0}^i| = 0 \tag{1.11}$$

Separation can be tested by these common factors. If separation occurs, any common factor of the i-th block should not be cointegrated of any j-th block (i, j = 1, 2). Therefore to test the separation hypothesis we have only to find cointegration in $(\gamma_{11}^{\perp\prime}X_{1t}, \gamma_{22}^{\perp\prime}X_{2t})$. If non-cointegration cannot be rejected, then one cannot find separation, either.

2. Empirical Results

A. Data Description

All data are quarterly and extend from 1959:1 to 1991:2. The set of variables studied consists of real GNP, real fixed investment, the interest rates on six month commerical paper and on six month Treasury bills, real corporate commerical paper outstanding, real bank loans to nonfinancial business, and real M2. Table 1 contains the complete list of variables. The variables from the real sector and interest rate sector are all from CITIBASE. The financial aggregates except for M2 are from the Flow-of-Funds reports of the Federal Reserve. "Commercial paper" represents the outstanding liabilities of nonfinancial corporate business in the form of commercial paper. "Bank loans" is the item "bank loans, not elsewhere classified" for nonfinancial business. The data for M2 are from CITIBASE. All variables except for interest rates are deflated by the implicit price deflator and are in logs. The CITIBASE variables are seasonally adjusted; the flow-of-funds variables are not adjusted.

B. Characterization of the System

The data are first analyzed to determine the best statistical approximation for the long-run components of the series. Table 2 displays the results of augmented Dickey-Fuller tests for each variable. The column labelled "optimal lags" shows the lags included in the tests, chosen using the procedure advocated by Campbell and Perron (1991), based on results by A. Hall (1990), with kmax=8 quarters. In no case can a unit root be rejected. The only variable with a relative low p-value (0.13) is the interest rate on commercial paper. Although the nonstationarity of interest rates is controversial, the rest of this paper will proceed under the assumption that the integratedness of interest rates is a good approximation to the data for the period under study.

Table 1
List of Variables Studied
1959:1–1991:2

(1) Real sector

y	log of real GNP
tfi	log of real total fixed investment

(2) Nominal interest rate sector

icp	interest rate on 6 month commercial paper
tbill	interest rate on 6 month Treasury bills

(3) Financial Aggregates

ccp	log of real corporate commercial paper outstanding
bl	log of real nonfinancial business bank loans
M2	log of real M2

Table 2
Augmented Dicky–Fuller Tests

Variable	Test statistic	p–value	Optimal lags
y	–1.57	0.49	8
tfi	–1.70	0.35	8
icp	–2.45	0.13	5
tbill	–1.85	0.40	3
ccp*	–1.76	0.45	4
bl*	–2.25	.20	7
m2	–1.65	0.52	1

* Seasonal dummy variables included in the regression.
y = log of real GNP
tfi = log of real total fixed investment
icp = interest rate on 6 month commercial paper
tbill = interest rate on 6 month Treasury bills
ccp = log of real corporate commercial paper outstanding
bl = log of real nonfinancial business bank loans
M2 = log of real M2

The next step in the analysis is to determine whether the variables share any common stochastic trends. The analysis is conducted using two different methods: (1) Johansen's (1988) cointegration test on the system of seven variables and (2) Engle-Granger cointegration tests on all bivariate combinations of the variables. While the Johansen method is perhaps the most natural for a system of this size, it is known that the results can be very sensitive to the number of lagged differences included in the vector error correction model (VECM). Thus, both methods will be used to study the problem. Table 3 shows the results for the sequence of hypothesis tests using Johansen's method. The first column shows the results when four lags are included in the VECM and the second column shows the results when eight lags are included. When four lags are included, the test statistics suggest that there are three separate stochastic trends. When eight lags are included, the results differ according to the significance level. At a ten percent significance level, the test statistics imply three stochastic trends, while at a five percent significance level, the results are marginally in favor of four stochastic trends. Taking the two sets of results in combination, it seems reasonable to characterize the system of seven variables as having three different stochastic trends, and hence four independent cointegrating vectors.

To cross-check the results, we ran bivariate Engle-Granger cointegration tests on the seven variables. The results of those tests are given in Table 4. The top number in each cell is the negative of the value of the test statistic. The number in parenthesis is the number of lags included in the test, chosen based on Campbell and Perron's (1991) procedure with kmax = 8. The number in cell i,j is from the regression of variable i on variable j. Ideally, the matrix should be symmetric.

Table 3
Johansen's Test on 7 Variable System

Trace Statistic (4 lags included)	Trace Statistic (8 lags included)	Null Hypothesis
0.412	0.374	There is at least 1 stochastic trend
8.829	4.372	There are at least 2 stochastic trends
25.356	13.559	There are at least 3 stochastic trends
49.129**	46.890*	There are at least 4 stochastic trends
79.135**	96.738**	There are at least 5 stochastic trends
111.906**	162.880**	There are at least 6 stochastic trends
163.750**	237.371**	There are at least 7 stochastic trends

Seasonal dummy variables were also included. ** denotes significant at the 5 percent level; * denotes significant at the ten percent level.

Table 4
Bivariate Engle–Granger Cointegration Tests

	icp	tbill	y	tfi	M2	ccp	bl
icp		4.97** (1)	2.89 (5)	2.93 (5)	2.97 (5)	2.93 (5)	2.83 (5)
tbill	4.79** (1)		2.74 (6)	2.90 (6)	2.83 (6)	2.46 (3)	2.28 (3)
y	1.45 (5)	1.29 (6)		4.75** (3)	3.31* (4)	3.45** (4)	2.37 (2)
tfi	1.94 (5)	2.02 (6)	5.03** (6)		4.52** (6)	4.05** (4)	4.04** (2)
M2	1.77 (5)	1.60 (3)	3.45** (4)	4.41** (6)		3.37* (4)	3.30* (3)
ccp	1.54 (2)	1.59 (2)	3.72** (4)	4.21** (4)	3.51** (4)		3.47** (4)
bl	1.65 (5)	1.71 (3)	2.51 (2)	4.07** (2)	3.35* (3)	3.34* (4)	

The top number is minus the value of the test statistic. The number in parenthesiss is the number of lags included in the test. All tests involving flow–of–funds data include seasonal dummy variables. ** denotes significant at the 5 percent level, * denotes significant at the 10 percent level. The critical values (from MacKinnon) are –3.079 at the 10%, –3.386 at the 5%, and –3.986 at the 1% significance levels.

y = log of real GNP
tfi = log of real total fixed investment
icp = interest rate on 6 month commercial paper
tbill = interest rate on 6 month Treasury bills
ccp = log of real corporate commercial paper outstanding
bl = log of real nonfinancial business bank loans
M2 = log of real M2

Consider first the results by sector. The relevant statistics appear in blocks on the diagonal of the table. The first two-by-two block on the diagonal forms the interest rate sector. Noncointegration can be rejected between the two interest rates at a high significance level. Thus, they appear to share a common stochastic trend. In the real sector, output and fixed investment also appear to have a common stochastic trend, since noncointegration is rejected at the one percent significance level. This result is consistent with the work of King, Plosser, Stock and Watson (1992). The last three-by-three block on the diagonal forms the financial aggregates sector. The evidence here suggests that the financial sector may contain only one stochastic trend. The hypothesis of non-cointegration is rejected at the five percent level in eight of the twelve cases, and at the ten percent level in the other four cases. Three of these four latter cases involve bank loans.

Are the stochastic trends common across sectors? The test statistics off the blocks on the diagonal in Table 4 lead to the following conclusions. First, the interest rate sector has a distinctly different stochastic trend from both the real and the financial aggregate sectors. In no case is either of the interest rate variables cointegrated with any other variable. On the other hand, the stochastic trend in the real sector seems to be the same as the stochastic trend in the financial aggregate sector. This conclusion is based on the strong evidence of cointegration between output or investment on the one hand, and commercial paper or M2 on the other hand. The result is weakened somewhat by the fact that although bank loans appear to be cointegrated with investment, one cannot reject noncointegration with output.

We now use the framework presented in the last section to conduct formal separation tests. The results are presented in Table 5. Three hypotheses are tested, corresponding to separation between pairs of the three sectors. Consider first the test of the null hypothesis of separation between the real sector and the interest rate sector. The test statistics (shown for both four and eight lags) indicate that the null hypothesis cannot be rejected. This result implies that the two sectors do not share a common stochastic trend. The second hypothesis deals with separation between the real sector and the financial aggregate sector. Here, the null hypothesis is resoundingly rejected. Thus, the two sectors do share a common long-run trend. By transitivity, the results of the tests of these two hypotheses should imply that the interest rate sector and the financial aggregate sector have separate trends. In fact, as shown in the third part of the table, the null hypothesis of separation between these two sectors is marginally rejected.

Except for the last result, the formal separation tests lead to the same conclusion as the bivariate Engle-Granger tests; that there is one stochastic trend underlying all of the variables in the real and financial sector and another trend underlying the interest rate variables. It is not clear why the third separation test leads to different results. One problem with the test is that the critical values are based on asymptotic distributions while the actual sample size is not particularly large.

Based on the set of results as a whole, it seems reasonable to characterize the system as having between two and three stochastic trends. If there are three stochastic trends, the one contained in bank loans is separate from the others. In any case, the interest rate sector also has a separate stochastic trend. There should be four or five independent cointegrating vectors associated with the system.

Table 5
Separation Tests

1. **Null Hypothesis: (y, tfi) has separate stochastic trend from (icp, tbill).**

    A. 4 lags included: q statistic = 0.195, p–value = 0.907

    B. 8 lags included: q statistic = 0.603, p–value = 0.740

2. **Null Hypothesis: (y, tfi) has separate stochastic trend from (ccp, bl, M2).**

    A. 4 lags included: q statistic = 25.363, p–value = 0.000

    B. 8 lags included: q statistic = 25.865, p–value = 0.000

3. **Null Hypothesis: (cp, tbill) has separate stochastic trend from (ccp, bl, M2).**

    A. 4 lags included: q statistic = 8.383, p–value = 0.040

    B. 8 lags included: q statistic = 6.704, p–value = 0.081

y = log of real GNP
tfi = log of real total fixed investment
icp = interest rate on 6 month commercial paper
tbill = interest rate on 6 month Treasury bills
ccp = log of real corporate commercial paper outstanding
bl = log of real nonfinancial business bank loans
M2 = log of real M2

There are several possible ways to estimate the cointegrating vector. While Johansen's (1988) method is superior asymptotically, it can have substantial bias in small samples (Ogaki and Park (1991)). On the other hand, Stock and Watson's (1991) dynamic OLS tends to behave well in small samples. Thus, we use the latter method. As it turns out, both give similar results.

Table 6 presents the estimates of five linearly independent cointegrating vectors and the names of the associated error correction terms. The cointegrating vectors were estimated using dynamic OLS, with the leads and lags chosen by setting kmax=8, and successively eliminating insignificant terms. The t-statistics reported incorporate HAC (heteroskedastic and autocorrolation consistent) standard errors, using a Parzen kernel with eight lags. Neither of the cointegrating vectors between the two interest rate variables or between real GNP and money were statistically different from (1,-1), so we imposed (1,-1) as the cointegrating vector.

Many of the error correction terms have economic interpretations. For example, the error correction term in the interest rate sector is simply the spread, while the error correction term between money and output is velocity. Further, the error correction term between commercial paper outstanding and bank loans is a nonlinear transformation of the mix variable of Kashyap, Stein, and Wilcox (1991). Moreover, these error correction terms can be combined in different ways to yield error correction terms with different interpretations. For example, linear combinations of the error correction terms in the table can lead to relationships between money and investment or between money and bank loans.

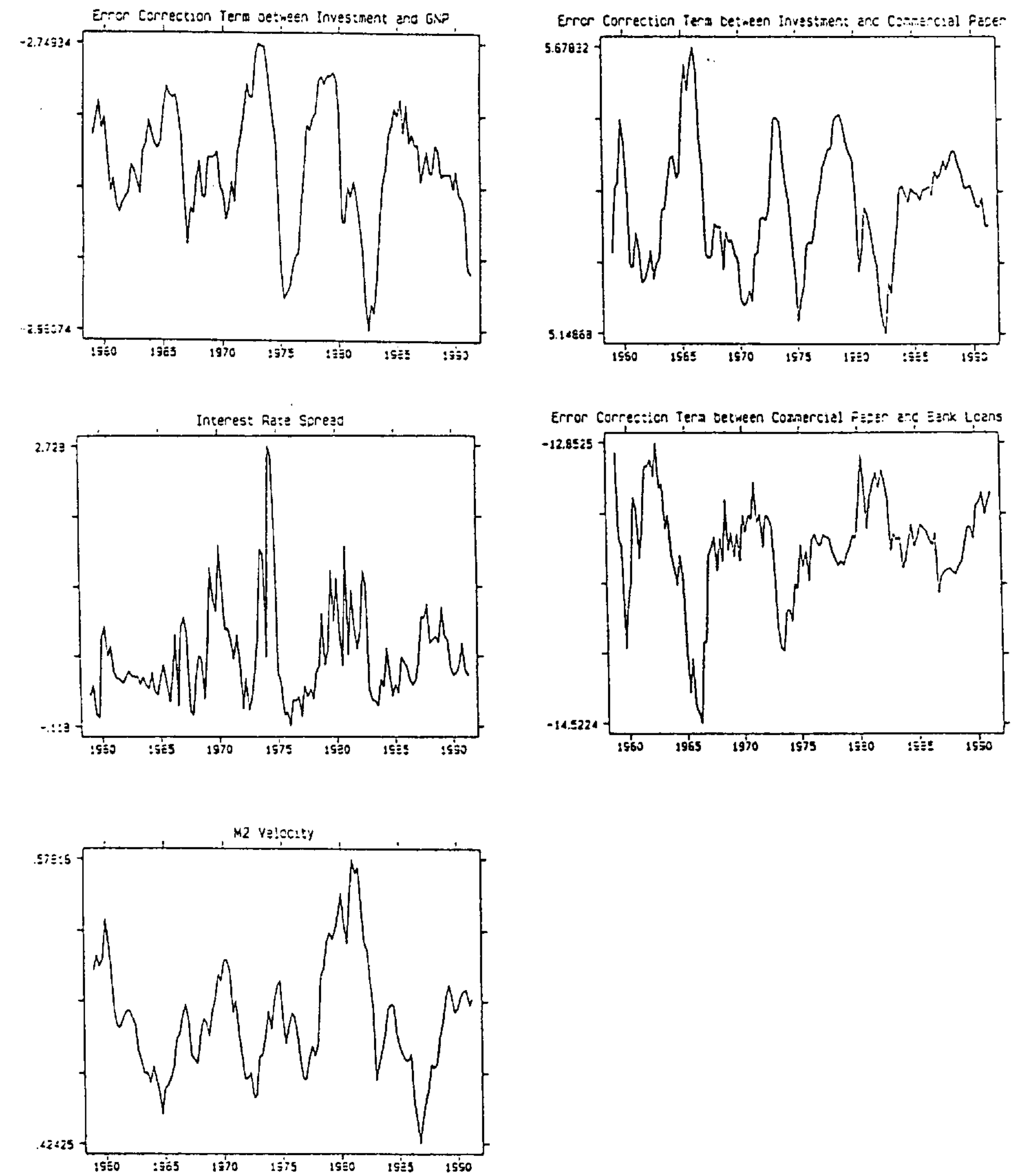
Figure 1 presents graphs of each of the five error correction terms. The top left graph

Table 6
Estimates of the Cointegrating Vectors and Error Correction Terms
Dynamic OLS

(1)	spread = icp − 1.024^{*} tbill (57.24)	6 leads, 8 lags
(2)	ziy = tfi − 1.128 y (58.85)	8 leads, 7 lags
(3)	velocity = y − 0.992^{*} m2 (61.31)	7 leads, 8 lags
(4)	zic = tfi − 0.251 ccp (17.42)	8 leads, 7 lags
(5)	zcb = ccp − 2.832 bl (15.17)	8 leads, 7 lags

All regressions also included constant terms. Those regressions involving flow–of–funds data also included seasonal dummy variables. * indicates that the value of the coefficient was not significantly different from −1, so it was set equal to −1 in the definition of the error correction term.

Figure 1


Error Correction Term between Investment and GNP
-2.74934
Error Correction Term between Investment and Commercial Paper
5.67832
5.14868
Interest Rate Spread
2.728
Error Correction Term between Commercial Paper and Bank Loans
-12.8525
-14.5224
M2 Velocity
.42425
1960
1965
1970
1975
1980

shows the error correction term between investment and GNP. The cyclical pattern of this term shows that investment tends to rise relative to GNP during expansions and fall during recessions. This pattern is unsurprising, given the stylized facts on the relative volatilities of investment and GNP. The second graph in the first column shows the spread. As demonstrated by many before us, the spread begins rising before the peak of every business cycle, with the exception of the 1990-91 recession. On the other hand, M2 velocity, which is shown on the bottom graph, also rises before every recession, including the 1990-91 recession. Graphs of the error correction terms involving commercial paper are shown in the second column. The peaks of the error correction term between investment and commercial paper coincide with the peaks of the investment-GNP term. The error correction term between commercial paper and bank loans generally rises before recession, but the pattern is not as clear as it is for the spread or for velocity. The rise of zcb before a recession is consistent with the pattern of Kashyap et al.'s mix variable.

C. The Relative Predictive Power of Financial Variables

In this section, we conduct significance tests for excluding sets of variables in order to see which have the most information for forecasting output and investment growth. We also examine the changing predictive power over different time periods. The general model, which has the growth rate of either output or investment as the dependent variable, contains a constant term, seasonal dummy variables, four lags of the dependent variable, four lags of each of the five error correction terms, and four lags of the change in the interest rate on commercial paper. Note that the lagged differences of any of the other variables are not linearly independent of the set of variables included. Table 7 shows the test statistics for excluding various groups of variables. The first column shows the variables excluded, the second gives the number of variables excluded, the third gives the test statistic, and the fourth gives the p-value.

Consider first the equations for output growth, shown in the top panel of Table 7. Both the spreads and all variables involving interest rates are highly significant. This result is consistent with earlier work on the predictive power of interest rate spreads output. Second, M2 velocity is also very significant, even in the presence of interest rates. On the other hand, the error correction terms between investment and output, between investment and commercial paper outstanding, and between commercial paper and bank loans are not significant by conventional measures. Thus, the key error correction terms are the interest rate spread and M2 velocity in terms of predictive power in the general model for output. the credit aggregates do not appear to have additional explanatory power.

The lower panel reports the results for investment growth. Here, only M2 velocity is significant by conventional measures. It is interesting to find that the interest rate variables are not jointly significant in the general model. After M2 velocity, the next lowest p-value is for the error correction term between investment and output, which has a value of 0.19. Although the four lags are not jointly significant, a modified model with only one lag of the error correction term between investment and output (not shown in the table) suggests that this term has some predictive power.[1]

[1]Modifying the model in this way for the other error correction terms did not significantly change their significance levels.

Table 7
A. Exclusion Tests for Predicting GNP Growth
1960:1 – 1991:2

Variables excluded	# of vars excluded	Test Statistic	p–value
spread(–1)– spread(–4)	4	5.348	0.001
spread(–1)– spread(–4) Δicp(–1)–(–4)	8	3.305	0.002
velocity(–1)– velocity(–4)	4	4.089	0.004
ziy(–1)–(–4)	4	0.934	0.448
zic(–1)–(–4)	4	0.138	0.968
zcb(–1)–(–4)	4	0.346	0.846

B. Exclusion Tests for Predicting Investment Growth
1960:1 – 1991:2

Variables excluded	# of vars excluded	Test Statistic	p–value
spread(–1)– spread(–4)	4	1.401	0.239
spread(–1)– spread(–4) Δicp(–1)–(–4)	8	0.812	0.593
velocity(–1)– velocity(–4)	4	2.684	0.036
ziy(–1)–(–4)	4	1.561	0.191
zic(–1)–(–4)	4	0.101	0.982
zcb(–1)–(–4)	4	0.144	0.965

The general model contains a constant, seasonal dummy variables, lags one through four of the dependent variable, spread(–1)–(–4), Δicp(–1)–(–4), velocity(–1)–(–4), ziy(–1)–ziy(–4), zic(–1)–zic(–4), zcb(–1)–zcb(–4).

Overall, of the five error correction terms studied, the interest rate spread, M2 velocity, and the error correction term between investment and output have some predictive power for either output or investment. The other balance sheet variables, such as bank loans and commercial paper, do not contain information beyond that contained in the interest rates and M2 velocity.

One of the issues discussed frequently in the literature is the changing predictive power over different sample periods. To investigate this issue for the variables contained in the model, we estimated three models for output growth and three models for investment growth. In every specification, only the first lag of M2 velocity was significant. Thus, each model contains only one lag of M2 velocity. For output, all three models contain four lags of output growth, seasonal dummy variables, and one lag of M2 velocity. Model 1 also contains one lag of the interest rate spread, Model 2 contains four lags of the interest rate spread, and Model 3 contains four lags each of the interest rate spread and the change in the interest rate on commercial paper. Thus, the three models differ only in the interest rate variables included. The three models for investment are identical, except that each model also contains one lag of the error correction term between investment and GNP.

The periods studied are (1) 1960:2 - 1991:2, (2) 1960:2 - 1969:4, (3) 1970:1 - 1979:4, (4) 1980:1 - 1989:4, and (5) 1960:2-1970:4, 1976:1-1991:2. The first time period represents the entire sample, and the second through fourth periods cover each of the decades. The motivation for the last time period will be discussed below.

The results are given in Table 8. Consider the results for output, given in Part A. For all specifications, both M2 velocity and interest rates are highly significant for predicting

Table 8

A. Predicting Real GNP Growth over Different Time Periods

All equations contain a constant, seasonal dummy variables, ΔGNP(–1)–GNP(–4), and the variables indicated below.

Variables excluded	1960:2–1991:2	1960:2–1969:4	1970:1–1979:4	1980:1–1989:4	1960:2–70:4, 1976:1–91:2
Model 1: velocity(–1), spread(–1).					
velocity(–1)	0.000	0.001	0.132	0.038	0.000
spread(–1)	0.000	0.442	0.002	0.271	0.163
Model 2: velocity(–1), spread(–1)–spread(–4)					
velocity(–1)	0.000	0.002	0.214	0.053	0.000
spread(–1)–spread(–4)	0.000	0.748	0.001	0.224	0.176
Model 3: velocity(–1), spread(–1)–spread(–4), Δcomm paper(–1)–Δcomm paper(–4)					
velocity(–1)	0.000	0.002	0.080	0.130	0.000
spread(–1)–spread(–4) Δcomm paper(–1)–Δcomm paper(–4)	0.000	0.794	0.006	0.027	0.083

output. The story changes substantially as the sample periods vary, though. First, during the 1960's, only M2 velocity is still highly significant; none of the interest rate variable groups is significant at any reasonable level. On the other hand, during the 1970's, all groups of interest rate variables are significant, while the p-values for excluding M2 velocity range between 0.08 to 0.214, depending on the specification. During the 1980's, M2 velocity is significant at the five percent level or better in two of the three cases, and at the 13 percent level in the third case. The spread terms by themselves are not significant. Only when the spread terms and the change in the interest rate on commercial paper are tested as a group is the group significant. Thus, the interest rate spread has superior predictive power in the 1970s, while velocity has superior predictive power in the 1960s and 1980s.

We then sought to determine whether the predictive power of the interest rate spread was confined to a particular portion of the 1970's. Through experimentation, we found that if we exclude only the period 1971:1 though 1975:4, then the significance of the spread decreases substantially.[2] The p-values are shown in the last column of Table 8. Thus, most of the significance of the interest rate spread comes from its dramatic behavior during the first half of the 1970s.

Part B of Table 8 conducts the same analysis for predicting real investment growth. The results here are similar, in that the spread only performs well in the 1970's. For investment, however, none of the variables performs particularly well during the 1980's.

To demonstrate further that M2 velocity is superior to the interest rate spread in

[2] The observations in 1975 are used for the lagged values of the variables in the forecasting equations.

Table 8
(continued)

B. Predicting Real Investment Growth over Different Time Periods

All equations contain a constant, seasonal dummy variables, Δinvestment(−1)–investment(−4), error correction between investment and GNP (−1), and the variables indicated below.

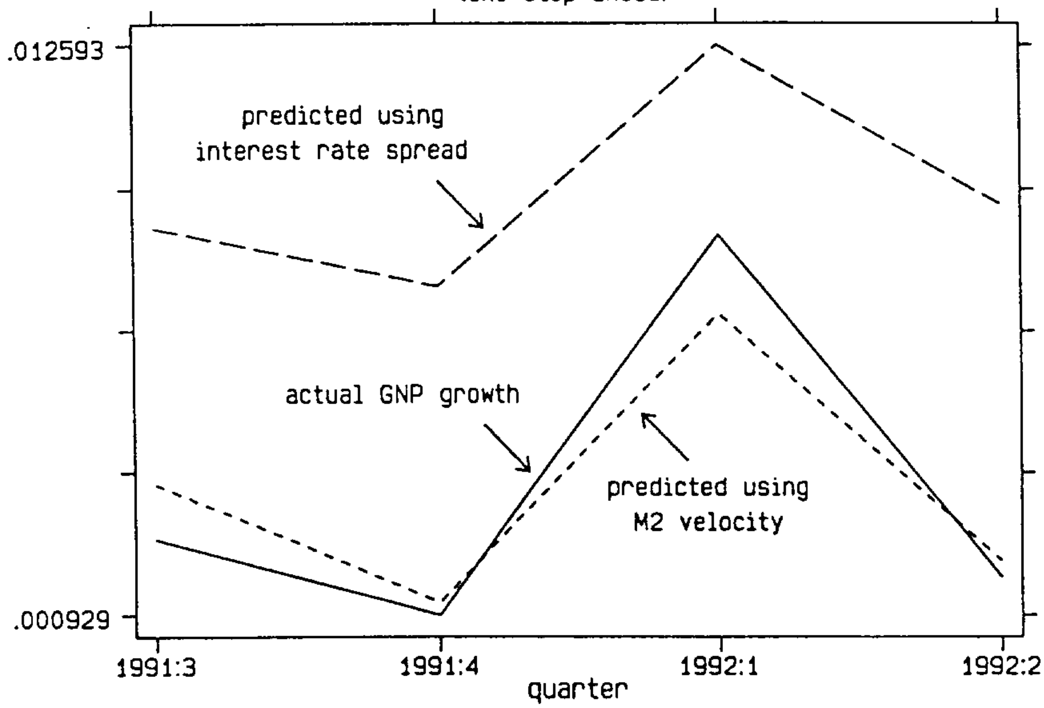
Variables excluded	1960:2–1991:2	1960:2–1969:4	1970:1–1979:4	1980:1–1989:4	1960:2–70:4, 1976:1–91:2
Model 1: velocity(−1), spread(−1).					
velocity(−1)	0.001	0.000	0.478	0.119	0.002
spread(−1)	0.012	0.454	0.003	0.138	0.152
Model 2: velocity(−1), spread(−1)–spread(−4)					
velocity(−1)	0.001	0.000	0.697	0.224	0.002
spread(−1)–spread(−4)	0.068	0.598	0.019	0.614	0.461
Model 3: velocity(−1), spread(−1)–spread(−4), Δcomm paper(−1)–Δcomm paper(−4)					
velocity(−1)	0.003	0.000	0.484	0.247	0.004
spread(−1)–spread(−4) Δcomm paper(−1)–Δcomm paper(−4)	0.197	0.391	0.044	0.341	0.633

predicting output, Figure 2 compares one-step ahead forecasts for four quarters that are out-of-sample, 1991:3 to 1992:2. Each equation regresses real GNP growth on seasonal dummy variables, four lags of GNP growth, and one lag of either the interest rate spread or M2 velocity. The graph shows clearly that the equation with M2 velocity predicts GNP growth very well, while the equation with the spread consistently overpredicts growth. The reason is simple. GNP growth was very low during this period, even though the interest rate spread was very low. On the other hand, M2 velocity was rising, and hence has predicted the slow GNP growth.

These results differ dramatically from those of Friedman and Kuttner (1992). In their study, they conclude that the spread is the only variable that consistently contains information about future movements in real income. Why are our results so different from theirs? The answer is simple. They include the period 1971:1 - 1975:4 in every subperiod that they study, and hence always find that interest rate spreads have predictive power. Because we also study periods that omit those five years, we find that the predictive power of the spread in the entire sample stems almost entirely from its outstanding predictive power during a five year period.

Another difference between our method and Friedman and Kuttner's method is our use of velocity as one of the monetary variables. Friedman and Kuttner argue that the relationship between various definitions of money (including M2) and income is not constant across the subperiods. Their conclusion is based on testing for unit roots or cointegration over various subperiods. These tests, however, have very low power. Shiller and Perron (1985) and Perron (1990) show that the power of tests of the unit root hypothesis depends

Figure 2: Out-of-Sample Forecasts of Real GNP Growth
(one-step ahead)



very importantly on the span of the data, rather than on the number of observations. The results of Stock and Watson (1992) demonstrate this point clearly in their analysis of the stability of the money demand equation for M1. Thus, Friedman and Kuttner's (1992) finding that M2 velocity is stationary over a thirty year period, but not over a twenty year subperiod is not very powerful evidence for instability.

3. Conclusions

This paper has investigated the relationship between a set of financial variables and real activity in a unified statistical framework. Cointegration analysis was used to identify the long-run and short-run linkages between different sets of variables. The method has proved fruitfull, for it has yielded new empirical results on the information contained in financial variables. In particular, the results suggest that M2 velocity bears a more stable relationship with output growth than does the spread between the interest rates on commercial paper and Treasury bills. Furthermore, the forecasting results for the last several quarters suggest that the breakdown in the relationship between GNP and M2 is greatly exaggerated.

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